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ABSTRACT

This paper describes four research examples of the use of prediction analysis in research. The aim of prediction analysis is to compare a rule as specified by a theory with a reference rule. The first example of prediction analysis in this paper concerns a study of 120 first, second, and third graders' performance on length and weight problems. Results showed that children would not be able to solve a weight problem at a given level if they did not solve the length task of the same and all lower levels. In the second example, the hypothesis that a certain amount of attentional capacity is a necessary condition for attaining certain forms of reasoning was tested and supported. In the third example, children solving a transitivity task were divided into two subpopulations: (1) an operational subpopulation, in which children infer judgments on the basis of premise relations; and (2) a nonoperational population, in which children infer judgments in some other way. The hypothesis that only the combination of these two populations produces stochastic dependence was supported. Data from the fourth study, whose 80 subjects had a mean age of 81 years, showed that it may not be meaningful to recode a continuous variable into two or more categories in order to apply prediction analysis. (SH)

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On the use of Prediction Analysis in cognitive-developmental research: Examples from childhood and old age

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The topic of this paper is the use of Prediction Analysis (Hildebrand, Laing, & Rosenthal, 1977; von Eye & Brandtstädter, 1983) in cognitive-developmental research. At the beginning, some of the most important properties of Prediction Analysis as a statistical method will be mentioned. In the main part, a series of three research examples will be described to illustrate the usefulness of Prediction Analysis in the context of Piagetian and NeoPiagetian research (Chapman & Lindenberger, 1988, 1989, in press; Lindenberger, 1985). Finally, I would like to present some recent work from the other end of the life span. This will also give me a chance to say something more general about the relationship between Prediction Analysis and cognitive-developmental theory.

The Method of Prediction Analysis

As a statistical method, Prediction Analysis is especially appropriate if the developmental theory guiding one's research makes strong assumptions regarding the implications among two or more categorical (qualitative, discrete) variables. Piagetian and NeoPiagetian theories clearly belong to this group. In most cases, these theories assume two things. First, they posit a set of discrete cognitive states or forms of reasoning. Second, they do not assume that all different forms of reasoning are present at birth or emerge in a random fashion. Instead, only a subset of all possible transitions between states over time is allowed by the theory.

Table 1 about here

Table 1 briefly summarizes the way in which propositions based on the type of theories just described are formulated in terms of Prediction Analysis. As an example, the proposition under investigation is the following: "No child who is unable to solve Task A is able to solve Task B." In other words, Task A is assumed to measure a form of reasoning that develops earlier than the

form of reasoning measured by Task B. The two-by-two contingency table represents all four possible combinations of passes and failures. Clearly, one combination is not permitted by theory. In the terminology of Prediction Analysis, this cell is called an "error cell."

In this situation, the aim of Prediction Analysis is to compare the rule as specified by the theory, Rule K, with some reference rule, Rule U. In most cases, Rule U will be estimated on the basis of marginal distributions under the assumption of independence. The measure of prediction success, DEL, is defined as unity minus the observed error rate divided through the expected error rate. The formula for the computation of DEL is provided in Table 1. The formula is remarkably simple. Of course, DEL also has a variance and a test statistic both of which are not displayed in the table.

Prediction Analysis has interesting features some of which are listed in Table 2. (a) It is very specific in the sense that it allows the researcher to specify error and hit cells according to the hypothesis that is to be tested. This also implies that Prediction Analysis is insensitive to data fluctuations that are irrelevant to the hypothesis under investigation. (b) DEL, the measure of prediction success, varies between 0 and 1 if the number of observed errors does not exceed the number of errors expected under Rule U. In this range, DEL can be interpreted as a PRE measure that tells you directly the proportion of error reduction under Rule K as compared to Rule U. (c) Prediction Analysis is applicable to very small samples with extreme variations in observed and expected cell frequencies. (d) Prediction Analysis can be extended to the multivariate case and to longitudinal data sets. For instance, one may emply second-order Prediction Analysis, where the entries of the contingency table refer to pairs of observations, rather than single observations.

Table 2 about here

Example 1

The first research example refers to the content décalage between transitive reasoning in the domain of length and transitive reasoning in the domain of weight (Piaget & Inhelder, 1941/1974). The term "transitive reasoning" is generally used to refer to forms of reasoning of the kind, "A is greater than B, B is greater than C, therefore, A is greater than C". In Piaget's terminology, this is a concrete operational form of reasoning.

In the study related to the first example (Chapman & Lindenberger, 1988; Lindenberger, 1985), we administered four length problems and three weight problems to a total sample of 120 first, second, and third graders, equally divided by sex and grade. Table 3 displays the measurement sequence observed for the length problem. "A" refers to an alternate version of the task which, according to our hypothesis, did not require the operational composition of premise relationships. Instead, we asumed that this version of the task could be solved by functional reasoniong of the sort, "things get bigger to the right", because the length of the comparison objects increased from left to right. The digits 3, 4, and 5 refer to three separate administrations of the standard task, one with 3, one with 4, and one with 5 comparison objects. In the standard version of the task, length relationships could not be inferred as a function of spatial position. Therefore, a greater number of sticks implied an increase in attentional demand because a greater number of premise relationships had to be combined to arrive at the correct solution. For all these reasons, we expected that the four tasks would form a perfect Guttman scale. As you can see in Table 3, this expectation was confirmed by the data. The situation was similar with respect to the weight tasks (Table 4).

Tables 3 and 4 about here

The cross-classification of length and weight problems is displayed in the Table 5. We expected that children would not be able to solve a weight

task of a given level if they did not solve the length task of the same and of all lower levels. The specification of error cells in the contingency table corresponds to this expectation. Compared to the number of errors expected under Rule U, our prediction led to a significant reduction of errors. However, one should note that the precision of our prediction was not very high; only about 22 out of 120 events were expected to fall in the error cells according to Rule U.

Table 5 about here

Example 2

The next example, which is based on data from the same subjects, is a test of the hypothesis that a certain amount of attentional capacity is a necessary condition for attaining certain forms of reasoning. This idea, which was formulated first by Pascual-Leone (1970), is a typical feature of NeoPiagetian theorizing (cf. Chapman, 1990). Specifically, it has been argued that three units of attentional capacity are necessary to attain the least demanding forms of concrete-operational reasoning: two units to attend to each of the two premises, and one unit to derive the conclusion.

In Table 6, measures of attentional capacity and three-term transitivity tasks are cross-classified to investigate this hypothesis. A combination of two measures, Backward Digit Span and the Figural Interscetions Test, was used as an index of attentional capacity. On the left hand side of the table, children with less than three units of capacity on both measures are compared with children with evidence in favor of at least three units of capacity on at least one of the two measures. The data were consistent with the hypothesis that at least three units of capacity are necessary to solve the tasks. The corresponding confidence intervals around the DEL values both excluded zero and included 1. Thus, the number of observed errors was not significantly greater than zero.

Table 6 about here

On the right hand side of the table, you see the results when a dichotomy of less than four versus four or more units of capacity is employed. This time, the DEL values were again different from zero, but they did not include 1. This was true both for the length and for the weight task. Thus, although the two tasks differed in overall difficulty, it does not appear to be plausible to explain this décalage in terms of a difference in capacity demands. [1]

Example 3

The last example from child development concerns the relationship between transitive reasoning and the memory for premise relationships. There has been some controversy over the nature of the relationship between memory for premises and judgments (Brainerd & Reyna, in press; Chapman & Lindenberger, in press). In particular, Brainerd and Kingma (1984) have argued that children actually may not reason on the basis of premises, but on the basis of a global representation of the task which is used to provide information both about the "premises" and the "conclusions."

One way to phrase the issue is to define the total population of children solving a transitivity task as a mixture of two subpopulations: (a) the operational subpopulation, where children infer their judgments on the basis of premise relations; (b) the nonoperational subpopulation, where children infer their judgments in some other way. According to this idea, which is illustrated in Table 7, only the combination of these two subpopulations produces stochastic dependence. Given that children in most studies on this topic are about 5 to 9 years old, and that operational forms of reasoning begin

[1] We have argued elsewhere (Chapman & Lindenberger, 1988) that the the décalage between length and weight is probably due to the erraneous application of functional reasoning. Specifically, children initially tend to construct differences in weight as a function of differences in size, in the sense that bigger things are heavier. It is only later that they begin to dissociate weight from size.

to develop during this age period, a mixture distribution of operational and nonoperational reasoners resulting in stochastic dependence should actually be the rule. However, if the operational subpopulation is small in comparison to the nonoperational subpopulation, this stochastic dependence may not be sufficient to reject the null hypothesis of independence between memory for premises and judgments. [2]

Table 7 about here

There are statistical methods available to estimate the relative size of mixture distributions (Erdfelder, 1990). In the present case, an empirical criterion was utilized as a basis for subdividing the total population into two subpopulations. Children with an operational justification of their judgments – "A is bigger than B, B is bigger than C; therefore, A is bigger than C" – were classified as operational reasoners (in the context of that particular task). By definition, al other children belonged to the nonoperational group.

The result of this splitting procedure is displayed in Table 8. Cell frequencies expected under Rule K were derived by multiplying the marginal probabilities of all three dimensions. In line with our hypothesis, the three cells qualifying as error cells were empty. Note that the stochastic dependency between memory for premises and judgments observed in the total sample was no longer present in the nonoperational subgroup.

Table 8 about here

Example 4: Limits to Prediction Analysis

The examples that I have presented so far demonstrate the usefulness of Prediction Analysis if the variables are truly categorical. From the perspective

[2] A more comprehensive account of this argument is found in Chapman and Lindenberger (in press).

of Piagetian theory, for instance, operational forms of reasoning are qualitatively different from developmentally prior forms of reasoning.

In contrast, it may not be very meaningful to recode a continuous variable into two or more categories in order to apply Prediction Analysis. Let me illustrate this with some recent data from my current work in the Berlin Aging Study.[3]

In Table 9, you see an analysis based on an initial data set of 80 research participants with a mean age of 81. According to the psychiatric diagnosis based on DSM III-R, 12 participants were at least mildly demented. Given that impairment in abstract thinking is one of the criteria leading to the diagnosis of dementia, we expected that these participants would perform poorly on the fluid ability markers of our test battery. (Note that the diagnosis of the psychiatrist was blind with respect to subjects' scores on the cognitive tests.) For the sake of the argument, I dichotomized the scores on the Letter Series test in three different ways: (a) a zero score versus the rest; (b) zero or 1 against the rest; (c) zero, 1, or 2 against the rest. The last dichotomy was associated with a significant DEL of 1.0. Now, there is nothing special about this particular dichotomy, at least as long as I have no theory for it, and a lot of information is lost by collapsing the continuous scale into two (or more) categories.

Table 9 about here

In reverse, it often makes sense to aggregate the kind of truly categorical data mentioned before. In our research on transitive reasoning in children mentioned before, for instance, we combined the five standard transitive

[3]The general goal of the Berlin Aging Study (BASE) is the multidisciplinary study of old age and aging in a sample of 600 randomly selected members aged 70 years and older. The measurement battery of BASE includes variables from internal medicine and geriatrics, psychiatry, psychology, and sociology. BASE is conducted by the Committee on Aging and Societal Development (AGE) of the Academy of Sciences and Technology in Berlin in collaboration with the Free University, Berlin, and the Max Planck Institute for Human Development and Education, Berlin, and is supported by the German Federal Department of Research and Technology (13 TA 011).

reasoning tasks to obtain a scale of proficiency in transitive reasoning (Lindenberger, 1985). This aggregate scale can then be used to investigate issues such as the interrelationship among different forms of concrete-operational thought or the relationship between age, attentional capacity, and cognitive development (Lindenberger, 1985; Little & Widaman, in press).

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Table 1

Prediction Analysis

Define ω_{ij} as indicator of error and hit cells:
$\omega_{ij} = 1$ if events in this cell are "errors" according to theory (i.e., Rule K)
$\omega_{ij} = 0$ if events in this cell are "hits" according to theory (i.e., Rule K)

DEL = 1 – (Rule K Errors / Rule U Errors)
DEL = 1 – (Observed Error Rate / Expected Error Rate)

$$DEL = 1 - \sum_{ij} \omega_{ij} \frac{f_{ij} / n}{f_{i.}/n * f_{.j}/n}$$

$$-\infty \leq DEL \leq 1$$

Scope: The proportion of the sample for which nontautological propositions are made.

Precision: The lower the expected error rate under Rule U, the lower the precision.

Task A (Developmentally Prior)	Task B: Pass	Task B: Fail
Pass	$\omega = 0$	$\omega = 1$
Fail	$\omega = 0$	$\omega = 0$

Table 2

Some Features of Prediction Analysis

Testing of specific hypotheses by specification of error and hit cells

Insensitive to data fluctuations irrelevant to the hypothesis

If errors under Rule K $\leq$ errors under Rule U, then $0 \leq DEL \leq 1$. In this case, DEL indicates the proportional reduction in error under Rule K as compared to Rule U (i.e., DEL is PRE measure).

Easy and straightforward to use

Applicable to very small samples with extreme variations in observed and expected cell frequencies

Applicable to the multivariate case

Applicable to conditional and unconditional designs

Related Methods

Binomial Probability Test

Configuration Frequency Analysis (von Eye. 1990)

Latent Attribute Models (Mokken scaling; multidimensional scaling; latent structure analysis; latent class analysis; analysis of finite mixtures)

Log-Linear Modeling with Design Matrices (Clogg, Eliason, & Grego, 1990)

Table 3

Table 1

Transitivity of Length

Obtained and Expected Frequencies

A	3	4	5	Obtained	Expected
0	0	0	0	1	0.4
1	0	0	0	64	55.5
0	1	0	0	0	0.4
0	0	1	0	0	0.1
0	0	0	1	0	0.0
1	1	0	0	41	47.0
1	0	1	0	0	7.3
1	0	0	1	0	1.4
0	1	1	0	0	0.1
0	1	0	1	0	0.0
0	0	1	1	0	0.0
1	1	1	0	11	6.2
0	1	1	1	0	0.0
1	0	1	1	0	0.2
1	1	0	1	0	1.2
1	1	1	1	3	0.2

Guttman coefficient of scalability: 1.00

Binomial probability: $p = 1.39 * 10^{-5}$

Note. N = 120. Theory-inconsistent patterns are underlined. Answers were considered correct when a correct judgment was followed by a valid justification.

Adapted from Chapman & Lindenberger (1988)

Table 4

Table 2

Transitivity of Weight

Obtained and Expected Frequencies

A	3	4	Obtained	Expected
0	0	0	72	48.4
1	0	0	14	31.2
0	1	0	1	19.1
0	0	1	0	3.9
1	1	0	24	12.3
1	0	1	0	2.5
0	1	1	0	1.6
1	1	1	9	1.0

Guttman coefficient of scalability: 0.98

Binomial probability: $p = 1.56 * 10^{-12}$

Note. N = 120. Theory-inconsistent patterns are underlined. Answers were considered correct when a correct judgment was followed by a valid justification.

Adapted from Chapman & Lindenberger (1988)

Table 5

Example 1: Cross-Classification of Profiles for Length and Weight Tasks

Hypothesis: Content Décalage Between Length and Weight

Profiles for Length Tasks	Profiles for Weight Tasks: 0 0 0	1 0 0	1 1 0	1 1 1	0 1 0	Total
0 0 0 0	1	0	0	0	0	1
1 0 0 0	53	9	1	0	1	64
1 1 0 0	17	3	21	0	0	41
1 1 1 0	1	2	2	6	0	11
1 1 1 1	0	0	0	3	0	3
Total	72	14	24	9	1	120

DEL = .91
$z = 4.73$; $p < .01$
Precision = .18

Note. Dark cells are error cells. All other cells are hit cells.

Adapted from Lindenberger (1985)

Table 6

Example 2: Cross-Classification of Concrete-Operational Tasks and Attentional-Capacity Measures

Hypothesis: Three Units of Attentional Capacity are Necessary to Solve Concrete-Opererational Tasks

Transitivity of Length (3-Term)

	Attentional Capacity $k \leq 2$	Attentional Capacity $k \geq 3$
Fail	13	52
Pass	1 (6.4)	54

DEL = .84
95 % CI = ± .31

	Attentional Capacity $k \leq 3$	Attentional Capacity $k \geq 4$
Fail	47	18
Pass	19 (30.3)	36

DEL = .37
95 % CI = ± .18

Transitivity of Weight (3-Term)

	Attentional Capacity $k \leq 2$	Attentional Capacity $k \geq 3$
Fail	13	73
Pass	1 (4.0)	33

DEL = .75
95 % CI = ± .49

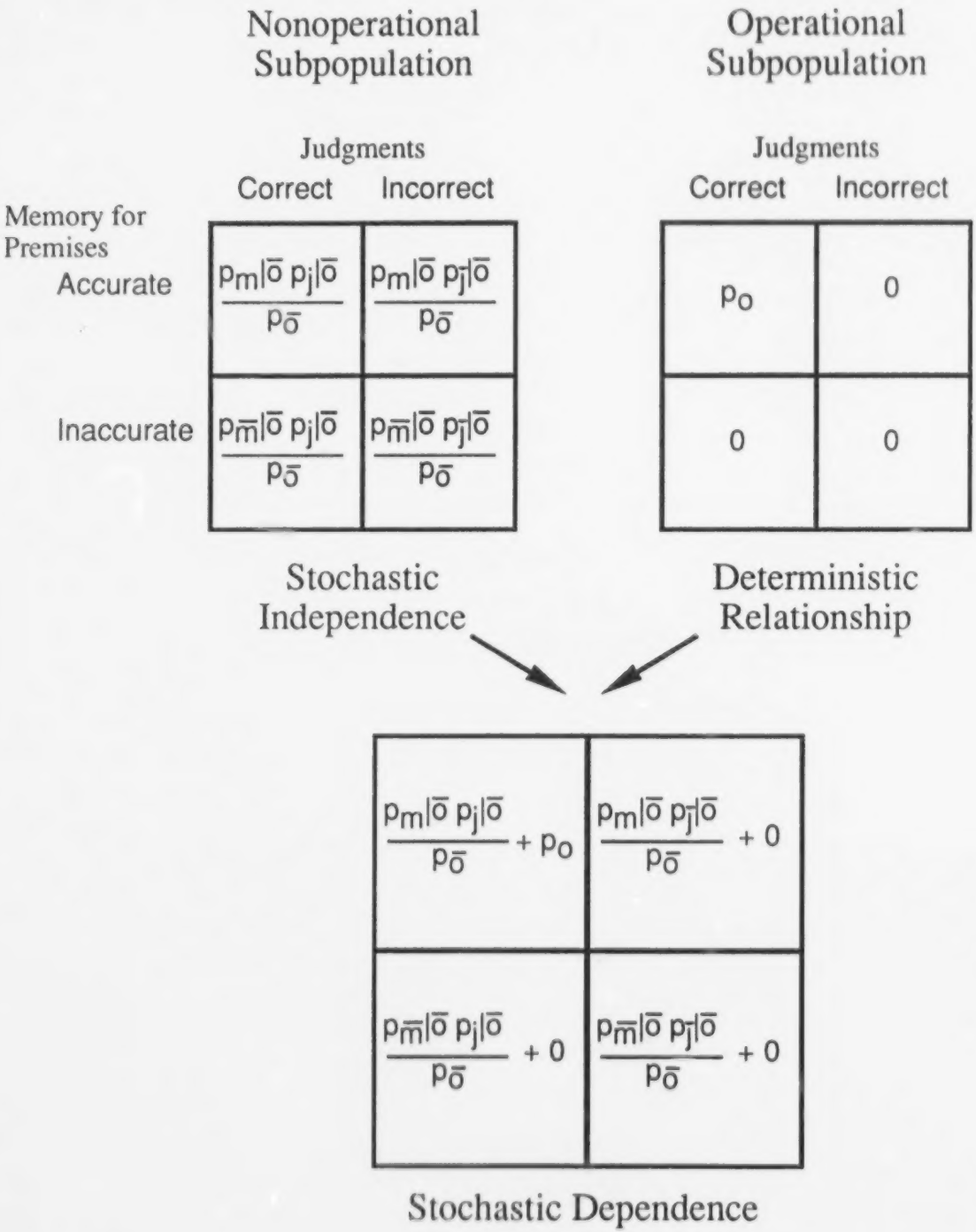
	Attentional Capacity $k \leq 3$	Attentional Capacity $k \geq 4$
Fail	58	28
Pass	8 (18.7)	26

DEL = .57
95 % CI = ± .25

Adapted from Chapman and Lindenberger (1989)

Table 7

Memory for Premises and Transitive Reasoning: A Distributional Model



Adapted from Chapman and Lindenberger (Developmental Review, in press)

Table 8

Example 3: Memory for Premises and Transitive Reasoning (3-Term Length Task)

Memory for Premises	Judgments: Correct	Judgments: Incorrect
Accurate	80	23
Inaccurate	7	10

$\chi^2(1) = 8.00$; $p < .01$

	Nonoperational Justifications: Correct	Nonoperational Justifications: Incorrect	Operational Justifications: Correct	Operational Justifications: Incorrect
Accurate	25	23	55	0 (13.0)
Inaccurate	7	10	0 (5.6)	0 (2.1)

DEL = 1.00; z = 4.89; p < :01

Chi-Square(1) for nonoperational submatrix: 0.24; n.s.

Adapted from Chapman and Lindenberger (Developmental Review, in press)

Table 3

Example 4: Psychiatric Diagnosis of Dementia and Performance on Fluid Intelligence Tests

Score on Letter Series Test	Psychiatric Diagnosis: Not Demented	Psychiatric Diagnosis: Demented	
0	12	1	
> 0	56	11 (10.1)	DEL = -.01 z = -.32; n.s.
0, 1	26	9	
> 1	42	3 (6.8)	DEL = .56 z = 1.51; .05 < p < .1
0, 1, 2	35	12	
> 2	33	0 (5.0)	DEL = 1.0 z = 2.30; p < .05